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Ambulance Demand Forecasting: A Systematic Review of Existing Models

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ABSTRACT

Forecasting ambulance demand is essential for improving Emergency Medical Services systems, guaranteeing prompt responses, and effectively allocating resources. With an emphasis on identifying important factors and their effects on demand, this systematic review offers an overview of the literature on forecasting ambulance demand. The goal of this study is to help increase the effectiveness and efficiency of ambulance services. The results highlight the importance of some factors in call center case volume, such as the day of the week, national holidays, and local disease incidence rates. Increased call volumes on weekdays highlight the necessity of accurate forecasting models that consider daily and weekly changes. In addition to temperature and relative humidity, weather factors such as wind speed and season also have a big impact. Additionally, seasonal patterns show that demand is higher in the winter, emphasizing the significance of seasonal adjustment in forecasting models. This review highlights the diversity of effective forecasting methods, with Artificial Neural Networks consistently emerging as the most effective approach. Tailoring forecasting models to local demographics and incorporating additional factors such as weather, air quality, and traffic patterns could enhance forecasting accuracy. This systematic review sheds light on the complex dynamics of ambulance demand forecasting, emphasizing the need for multifaceted models that adapt to diverse contexts. Accurate forecasts are crucial for optimizing emergency service resources, ultimately leading to improved patient care and more efficient healthcare systems. Future research should continue to explore these intricate relationships to advance the field and contribute to more effective ambulance services.

1. INTRODUCTION

Emergency Medical Services (EMS), often known as ambulance, paramedic, or pre-hospital emergency services, are essential for providing communities with immediate medical care (Ingolfsson, 2013; Martin et al., 2021). EMS is essential for maintaining public health and ensuring prompt medical care in life-threatening situations. Especially for high-priority calls, EMS services are challenged with the ever-evolving problem of efficiently allocating ambulances and medical professionals needed to ensure adequate geographic coverage. Minimizing response times to life-threatening crises while maintaining low operational expenses is one of the main objectives of EMS (Zhou and Matteson, 2016). To accomplish these objectives, EMS managers and dispatchers carefully analyze how incoming call requests (demand) are distributed and they create resource deployment plans that describe the number of ambulances and emergency response staff needed for upcoming times (Martin et al., 2021).

Ambulance services are an integral component of EMS, playing a pivotal role in the continuum of healthcare delivery during emergencies. These services are designed to provide immediate medical assistance and transport to individuals facing life-threatening situations or requiring urgent medical attention. Whether responding to accidents, medical emergencies, or disaster scenarios, ambulance services are at the frontline of EMS, functioning as the initial link in the chain of care that aims to save lives and mitigate the impact of health crises in communities. They play a critical role in enhancing patient outcomes and improving the overall efficiency of emergency medical care systems through prompt response and competent interventions.

Accurate demand forecasting is a key component in the effective operation of EMS systems. Predicting the number and type of medical emergencies that will require attention is fundamentally the science and art of EMS within a given region, timeframe, or scenario. Forecasting ambulance demand is crucial for modern healthcare and emergency services. It enables healthcare institutions to proactively manage resources, optimize response times, and improve overall patient care by accurately forecasting the volume, timing, and geographic distribution of ambulance calls. Emergency service providers may strategically arrange ambulances using this forecasting technique, ensuring that vital medical assistance is accessible when and where it is most needed. In addition, it enables effective staff deployment, speeding up response times, and perhaps even saving lives in time-critical circumstances. Forecasting ambulance demand also helps with resource management, cost reduction, and the creation of focused public health initiatives. The bottom line is that it is an essential instrument that not only increases the effectiveness of emergency medical services but also promotes community wellbeing by ensuring that healthcare resources are used effectively and quickly.

Population increase and aging trends indicate a rising global need for these services (Nicoletta et al., 2022). Emergency call centers must deal with significant daily and seasonal variations that may seem excessively unpredictable at the same time as the annual increase in activity (Viglino et al., 2017). Forecasting ambulance demand is a complex field that considers various variables, including geographic differences, data sources, explanatory variables, covariables, and forecasting techniques. The accuracy of forecasting models depends on knowing how explanatory variables and covariables impact ambulance demand and including them in the models. For efficient resource allocation and quick responses to medical emergencies, a thorough understanding of the factors influencing demand is required. Across studies, the factors chosen can differ significantly. Poor deployment decisions can be made because of the use of incorrect variables, which will lower performance (Matteson et al., 2011).

It is a constant struggle to pinpoint the crucial factors and comprehend how they affect demand. Researchers should aim to standardize the selection and evaluation of these variables. However, a variety of research findings characterize ambulance demand forecasting, and systematic reviews are particularly valuable in complex fields like this, where a rigorous and structured approach is needed to analyze and compare diverse studies. This systematic review aims to highlight the similarities and differences across this body of research. This systematic review aims to present a comprehensive and up-to-date overview of the current state of research in the field, identify research gaps, and provide insightful contributions to enhance the effectiveness and efficiency of EMS systems, with a specific focus on ambulance services.

2. METHOD

The systematic review method was used for data collection, analysis, interpretation, and presentation. By determining if research findings are consistent and generalizable and, if not, why, systematic review methodology can manage potentially “unmanageable amounts of information” and rationalize existing evidence effectively (Torgerson, 2003). The study was conducted and reported in accordance with the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) Statement (Moher et al., 2009). Five databases were searched, and different combinations of the specified keywords were searched in the titles, abstracts, and keywords of the studies. The goal was to compile and comprehensively analyze the research findings without limiting publication years, while bearing in mind that the search strategy deadline was set at 2022. The details on searched databases, keywords, and inclusion criteria are detailed in Table 1, and the flowchart prepared according to the PRISMA Guidelines that shows the study selection is presented in Annex-1.

Table 1. Search Strategy for the Review

Databases	EBSCO*, MEDLINE/PubMed, ScienceDirect, Scopus, Web of Science Core Collection
Keywords	Ambulance, arrivals, call, demand, emergency, emergency call, EMS, predict or forecast
Inclusion Criteria	Published in a peer-reviewed journal English or Turkish Having studied the forecasting of emergency call volumes Research article Availability of the full text

*EBSCO: EBSCO offers access to numerous databases, such as Business Source Ultimate, ERIC, and Social Sciences Index Retrospective.

EndNote 20, a database application used to store and manage bibliographic information and retrieve data, was used to extract studies from databases, and duplicates were detected by combining the libraries created for each database. Then, the titles and abstracts of the studies were examined one by one; studies published in peer-reviewed journals in Turkish or English, containing the forecasting of emergency call volume, and whose full text can be accessed, were included in the scope of the review. To access studies that are not listed in electronic databases, it is recommended to scan the bibliographies of the studies accessed (Horsley et al., 2011). In this regard, the bibliographies of the studies were scanned using the snowball method, and articles that were not included in the databases were also accessed. As a result of the screening, 24 studies that were determined to comply with the relevant criteria were included in the scope of review (Annex-1). To strengthen credibility and confirmability in this study, the research method, data, findings, and results are explained in a way that researchers can benefit from, all studies accessed are stated in the appendix with their sources, analyzed in an impartial and unbiased manner, and rearrangements were made when necessary. The studies included in this study were coded into a database created by the researcher using Microsoft Office Excel according to the determined categories.

The scope of the review encompasses an evaluation of various aspects of EMS demand forecasting research, including but not limited to the geographical context (country), methodological approaches used, software tools utilized, data duration, range of explanatory variables considered, covariables accounted for, and techniques for measuring forecast accuracy. Table 2 provides a list of the acronyms used in this paper, which enhances comprehension of the study’s key elements.

Table 2. Acronyms used in this study

Acronym	Full Form
AAPE	Average Absolute Percentage Error
ANLS	Average Negative Log Score
ANN	Artificial Neural Network
ARIMA	Autoregressive Integrated Moving Average
CCE	Categorical Cross-Entropy
GAM	Linear Generalized Additive Model
GDX	Gradient Descent with Momentum and Adaptive Learning
GMM	Gaussian Mixture Model
KDE	Unwarped Kernel Density Estimation
LightGBM	Light Gradient Boosting Machine
LSTM	Long Short-Term Memory
MA	Moving Average
MAD	Mean Absolute Deviation
MAE	Mean Absolute Error
MAPE	Mean Absolute Percentage Error
MEANS	Means with Simple Moving Average Model
MHF	MEDIC Hourly Forecasting
MLP	Multi-layer Perceptron
MRAE	Mean Relative Absolute Error
MSE	Mean Squared Error
NormRMSE	Normalized Root Mean Square Error
OYL	One Year Lag
RAW94	Raw Observations Model
RBFN	Radial Basis Function Network
RMSE	Root Mean Square Error
RSS	Residual Sum of Squares
SARIMA	Seasonal Autoregressive Integrated Moving Average
SMA94	Simple Moving Average Model
SSA	Singular Spectrum Analysis
SVR	Support Vector Regression
WAPE	Weighted Absolute Percentage Error
ZOR	Zero/One Regression
ZORA	Zero/One with Adjustment

3. FINDINGS

3.1. Descriptive Findings

Studies included in the systematic review were assessed on the basis of predetermined criteria. The studies were first examined and summarized by the author, year, country where the study was conducted, scale of the study, method, software, data duration, explanatory variables, covariables, and forecast accuracy measurement. Next, common findings obtained from studies on emergency demand forecasting were examined in detail (Annex-2).

The examined studies were published between 1985 and 2022. In terms of country distribution, the United States ranked first (n=4; 17%), followed by Taiwan and Canada, which tied for second place (n=3; 13% each). Among other countries, there were also studies conducted in Australia, the United Kingdom, Türkiye, and several more. The studies encompassed various scales, including city (n=16, 67%), country (n=3, 13%), and several other scales such as county, EMS station, hospital, region, and state (n=1; 4% each).

The studies used various methods for forecasting, with ARIMA being the most employed (n=9, 13%). Other frequently used methods include ANN (n=6, 8%), MA (n=4, 6%), Holt-Winters (n=3, 4%), MHF (n=3 studies, 4%), MLP (n=3, 4%), and several other methods such as regression (2 studies, 3%), SARIMA (2 studies, 3%), SSA (2 studies, 3%), SVR (n=2; 3% each) and more. In total, 45 different methods were employed across the studies, with the number of methods used in a single study ranging from one to six, averaging approximately three methods per study.

The studies employed various software tools for analysis, with R (n=5, 18%) and Python (n=4, 14%) being the most frequently used, followed by SAS (n=3, 11%), MATLAB (n=2, 7%), Microsoft Excel (n=2, 7%), SPSS (n=2, 7%), and a variety of other software tools including Caterpillar-SSA, FORTRAN, MATLAB, Minitab, Stata (n=1; 4% each). Additionally, there were six studies (21%) in which the software used was not mentioned.

The studies used various methods for forecast accuracy measurement such as MSE (n=7, 16%), MAPE (n=6s, 14%), Root Mean Squared Error (RMSE) (n=6, 14%), MAE (n=5, 12%), as well as various other methods such as Linear regression (n=2, 5%), AAPE, ANLS, Bias, CCE, Correlation coefficient, MAD, MRAE, Monthly bias range, NormError Percentage, NormRMSE, paired sample t-test, residual standard deviation, and WAPE, each used in one instance (2% each). In total, the forecast accuracy measurement methods used in the studies varied from one to four, with an average of approximately two forecast accuracy measures per study.

Studies used ANN employed various transfer functions, including Log-Sigmoid, Sigmoid, Hyperbolic tangent, ReLU. The number of hidden layers in the ANN configurations ranged from one to two, and the number of neurons in these hidden layers varied, with values of four, six, 22, and 64 used in different studies. In addition, diverse learning algorithms were utilized, such as GDX, backward propagation, forward feeding multilayer perceptron, backpropagation learning, and backpropagation with gradient descent.

3.2. Interpretive Findings

Upon deeper analysis, more specific findings regarding EMS demand forecasting were revealed. For EMS demand forecasting, the duration of the data used for forecasting varies, with the minimum period being one month, the maximum extending up to ten years, and the average duration falling around 3.25 years. The dataset allocation for training, testing, and validation in the included studies varied. Allocations included 50% training and 50% testing in one study, 57% training and 43% validation in another, and 60% training with 20% testing and 20% validation in a different study. There were also variations such as 67% training and testing with 33% validation, 70% training with 20% validation and 10% testing, and 72% training with 28% testing. Additionally, some studies employed allocations such as 80% training and 20% testing, 90% training and 10% validation, and k-fold cross-validation, whereas nine studies did not mention the dataset allocations. The approximate average allocation for the training datasets across these studies is approximately 72.43%.

The studies included various explanatory variables, with a notable emphasis on day of the week (n=15, 30%), followed by month of the year (n=10, 20%), hour of the day (n=9, 18%), and season (n=4, 8%). In addition, special days or holidays, week of the year, and other variables were used to a lesser extent in the analyses. In total, the use of explanatory variables in the studies ranged from zero to five, with an average of two explanatory variables per study. Covariables included rainfall (n=3, 14%), daily COVID-19 admissions (n=2, 9%), temperature (n=2, 9%), and a variety of other factors such as cloud cover, daily COVID-19 incidence, daily deaths among COVID-19 patients, emergency type (hyperglycemia or hypoglycemia), gender, GIS-based location, humidity, incidence rate of acute gastroenteritis, incidence rate of chicken pox, incidence rate of influenza, pollen level, population, regional socioeconomic data, total number of people aged 50 and above, wind speed, and instances where covariables were not applicable (n=15, 68%). In total, the covariables used in the studies ranged from zero to five, with an average of approximately two covariables per study. The minimum duration of the data used was three months, the maximum duration was ten years, and the average duration was approximately four years.

In the reviewed studies, the best forecasting methods and their order of effectiveness varied across different scenarios. For instance, ANN was identified as the best method, followed by ARIMA. For shorter-term forecasts of one to six months, ARIMA and seasonal adjustment models performed well, and the linear regression model outperformed them for longer-term forecasts of more than six months. Smoothed average demand ranked highest, and LightGBM and Linear Regression were equally effective. SSA was the preferred method, followed by ARIMA and Holt-Winters. MLP was also noted as a strong method. Other methods such as SARIMA, MEANS, ZORA, and SVR were evaluated as best in their respective contexts, demonstrating the diversity of effective forecasting approaches.

The key findings derived from the studies reviewed are summarized as follows:

- There is a clear trend of higher call volumes on weekdays compared to weekends.
- The busiest hours for ambulance demand typically fall between 10 a.m. and 4 p.m. although this pattern can vary between weekdays and weekends.
- Weather factors were found to be associated with ambulance demand, with lower temperatures, higher wind speeds, and higher relative humidity negatively affecting demand during cooler months and the opposite effect during hotter months.
- Seasonal patterns in ambulance demand were observed, with the winter months generally showing higher demand.
- There is a meaningful correlation between EMS calls and subsequent intensive care unit admissions, particularly when considering a seven-day time frame.
- The effectiveness of forecasting models varied by location, with certain models outperforming others in specific areas.
- ANN has consistently emerged as the best-performing method for ambulance demand forecasting in several studies.
- MLP models consistently produced more accurate predictions in various situations.
- Time series analysis was found to provide powerful short-range forecasts of ambulance service needs, often outperforming more complex methods.

4. CONCLUSION

The systematic review of studies on EMS demand forecasting has been believed to provide valuable insights into the complex dynamics of this critical area of emergency services. A comprehensive examination of these studies revealed several key findings and trends that contribute to a deeper understanding of the factors influencing EMS demand.

The identified factors, including the day of the week, the presence of public holidays, and regional disease incidence rates, have consistently emerged as significant contributors to call center case volume. These findings emphasize the critical role of external variables in ambulance demand forecasting models, enabling effective capture of these dependencies. Most studies have used the time of day as their only factor and have produced forecasts for huge geographic areas like entire counties or entire cities (Martin et al., 2021). This reveals a potential gap in research when considering other dimensions or refining the geographic granularity of forecasting models. Researchers may need to explore additional factors or smaller-scale predictions to provide more precise and comprehensive insights in the field of study.

A clear trend emerged, with higher call volumes observed on weekdays than on weekends. Although this trend varied between weekdays and weekends, the peak hours for EMS demand were frequently between 10 a.m. and 4 p.m. This temporal variability highlights the necessity for precise forecasting models that account for daily and weekly fluctuations. Weather factors also played a significant role, with temperature, wind speed, and relative humidity influencing ambulance demand, especially during different seasons. Seasonal patterns indicated that winter months typically experienced higher demand, emphasizing the importance of seasonal adjustment in forecasting models. By doing this, medical professionals and emergency responders may more effectively foresee and get ready for the increased demand during these colder months.

Different areas within a city or region may have unique demand patterns, and understanding local demographics can help tailor forecasting models to these variations. Thus, considering the underlying population geography, demographic data, and population shifts and densities in future research is crucial. Beyond demographic variables, additional factors from various external data sources, such as weather conditions, air quality, traffic patterns, accidents, and some economic variables that could impact ambulance demand, should be included in the forecast model to enhance the forecasting accuracy.

The review also highlighted the diversity of effective forecasting approaches, with different methods performing optimally in distinct scenarios. ANN consistently proved to be the most effective method, with MLP models following closely behind, demonstrating their ability to adeptly capture the complexities of ambulance demand. This finding emphasizes how crucial it is to compare several forecasting approaches and select the one that is most appropriate for the characteristics and difficulties of a specific situation.

The reviewed studies identified several common limitations in most of the research findings. One of the frequently mentioned limitations was the exclusion of variables that can affect ambulance demand, including air quality, humidity, temperature, socio-demographic factors, ambulance availability, epidemics, cultural or sports events and traffic congestion. The exclusion of such important variables could lead to incomplete or inaccurate forecasts. To overcome this limitation, data granularity can be improved by capturing variety of variables which affect the ambulance demand. Another common limitation was the reliance on data from a single year. Using data from multiple baseline years could provide a more robust foundation for forecasting.

In essence, the findings from these studies underscore the multifaceted nature of ambulance demand forecasting. Future research in this field should continue to explore the intricate relationships between various factors and develop forecasting models that are adaptable to different contexts. Accurate and timely forecasts are crucial for optimizing emergency service resources, ultimately leading to improved patient care and more efficient healthcare systems.

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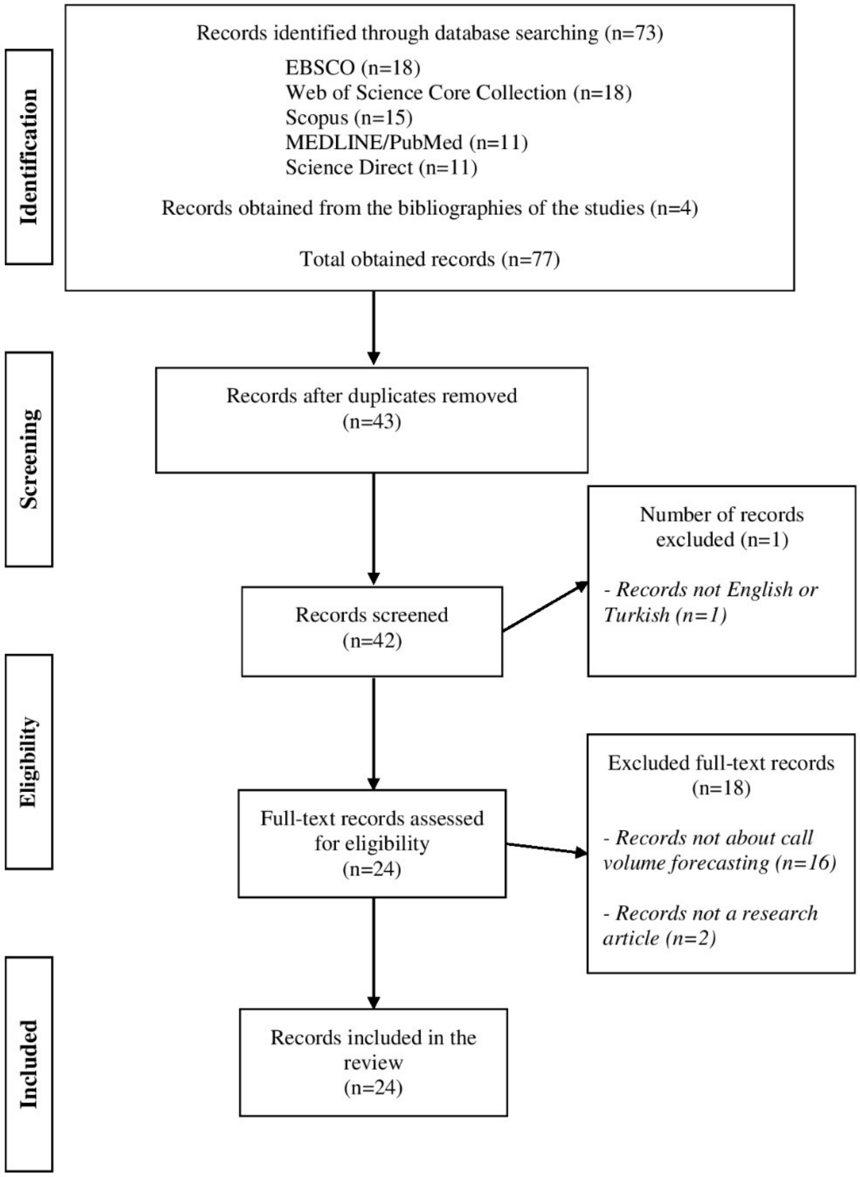
Annex-1. Study Selection Flowchart According to PRISMA Guidelines



Annex-2. Summary of articles evaluating EMS demand forecasting

Authors, year	Country	Study Scale	Method(s)	Software(s)	Data Duration	Explanatory Variable(s)	Covariable(s)	Forecast Accuracy Measurement(s)
(Mabert, 1985)	USA	City	ARIMA, Multiplicative/Additive, Multiplicative/Additive with Adjustment, OYL, ZOR, ZORA	SPSS	5 months	Day of the week Hour of the day Month of the year Season Special day/Holiday	N/A	MAPE Monthly Bias Range Residual Standard Deviation
(Baker and Fitzpatrick, 1986)	USA	City	Goal Programming, Quadratic Programming, Winter's Model	Not mentioned	3 months	Day of the week	N/A	Bias MSE
(Tandberg et al., 1998)	USA	City	ARIMA, MEANS, RAW94, SMA94	Not mentioned	18 months	Day of the week Hour of the day	N/A	Linear Regression RSS
(Brown et al., 2007)	USA	Country	Demand Pattern Analysis	Not mentioned	73 weeks (1 year 4 months)	Hour of the day	N/A	Percentage of accurate predictions
(Channouf et al., 2007)	Canada	City	ARIMA, Regression	R SAS	5 years	Day of the week Hour of the day Month of the year Special day/Holiday	N/A	MRAE RMSE
(Setzler et al., 2009)	USA	EMS Station	ANN, MHF	SAS	3 years	Day of the week Hour of the day Month of the year Season	N/A	MSE
(Matteson et al., 2011)	Canada	City	Dynamic Latent Factor Model, Integer-Valued Time Series	R	2 years	Day of the week Week of the year	N/A	RMSE

Authors, year	Country	Study Scale	Method(s)	Software(s)	Data Duration	Explanatory Variable(s)	Covariable(s)	Forecast Accuracy Measurement(s)
(Vile et al., 2012)	Wales/ United Kingdom	Country	ARIMA, Holt-Winters, SSA	Caterpillar-SSA	5 years	Day of the week Month of the year	N/A	RMSE
(Aydemir et al., 2014)	Türkiye	City	ANN, ARIMA, Trend Analysis	MATLAB	1 month	Day of the month	N/A	MAPE
(Chen and Lu, 2014)	Taiwan	City	ANN, MA, Regression, SVR	Not mentioned	3 years	N/A	GIS-based location	MAPE
(Chen et al., 2016)	Taiwan	City	ANN, MA, Sinusoidal Regression, SVR	MATLAB	3 years	Day of the week Hour of the day Month of the year Rush Hour Weekend	Rainfall	MAPE
(Vile et al., 2016)	Wales/ United Kingdom	Country	ARIMA, Holt-Winters, SSA	Microsoft Excel	5 years	Day of the week Month of the year	N/A	RMSE
(Zhou and Matteson, 2016)	Australia	City	GMM, Kernel Warping Method, MHF, KDE	Python	2 years	N/A	N/A	ANLS RMSE
(Viglino et al., 2017)	France	Hospital	GAM	R SAS	4 years	Day of the week Special day/Holiday Week of the year	Incidence of acute gastroenteritis Incidence rate of chicken pox infection Incidence rate of influenza Pollen level	Comparing prediction with real data on the cut-off of 100 cases

Authors, year	Country	Study Scale	Method(s)	Software(s)	Data Duration	Explanatory Variable(s)	Covariable(s)	Forecast Accuracy Measurement(s)
(Villani et al., 2017)	Australia	State	ARIMA, SARIMA	Stata	7 years	N/A	Emergency type (Hyperglycemia or Hypoglycemia) Gender	MAE MAPE MSE
(Wong et al., 2017)	China	City	ARIMA, Seasonal Adjustment Based on the Last Three Observations, Simple Linear Regression	SPSS	10 years	Month of the year Season	Cloud cover Humidity Rainfall Temperature Wind speed	AAPE
(Tsai et al., 2018)	Taiwan	City	90th Percentile for Ranked Demand, Average Demand, Average Demand Smoothed, Average Peak Demand, Average Peak Demand Smoothed	Not mentioned	1 year	Day of the week Hour of the day Week of the year	N/A	NormError Percentage NormRMSE
(Grekousis and Liu, 2019)	Greece	City	ANN	Not mentioned	Not mentioned	N/A	N/A	Correlation Coefficient MSE
(Lin et al., 2020)	Singapore	City	LightGBM, Linear Regression, MA, MLP, RBFN, SVR	Python	10 years	Day of the month Day of the week Month of the year	Regional socioeconomic data Total number of people aged 50 years and above	MAE MSE WAPE
(Mapuwei et al., 2020)	Zimbabwe	City	ANN, SARIMA	Minitab	8 years	N/A	N/A	MAE MSE Paired Sample t-test RMSE

Authors, year	Country	Study Scale	Method(s)	Software(s)	Data Duration	Explanatory Variable(s)	Covariable(s)	Forecast Accuracy Measurement(s)
(Hermansen and Mengshoel, 2021)	Norway	City	LSTM, MLP	Python	4 years	Day of the week Hour of the day Month of the year	Rainfall Temperature	Categorical Cross-Entropy MSE MAPE
(Martin et al., 2021)	USA	Country	ARIMA, Holt-Winters, MHF, MA, MLP	Python	8 years	Day of the week Month of the year Season	N/A	MAD MAPE
(Nicoletta et al., 2022)	Canada	City	Bayesian Generalized Linear Model, Markov Chain Monte Carlo	R	1 year	Day of the week Demand zones Hour of the day Special day/Holiday	Population	MAE Empirical Coverage
(Vinci et al., 2022)	Italy	Region	Multiple Linear Regression	Microsoft Excel	2 years	N/A	Daily COVID-19 admissions Daily COVID-19 admissions in Intensive Care Units Daily COVID-19 incidence Daily deaths among COVID-19 patients	Linear Regression